Restoration and Postprocessing of optical flow

Project: C. Garbe, P. Preusser, M. Rumpf
Overview

Part I (R.)
- Mumford Shah for image and motion restoration
- joint motion segmentation and deblurring
- total variation image and motion restoration

Part II (Claudia Kondermann)
- confidence measures
- reconstruction of flow fields
variational methods

[Horn, Schunk ´81] quadratic variational problem

[Nagel, Enkelmann ´86] anisotropic smoothing based on the structure tensor

[Schnörr ´94] nonlinear models

[Odbez, Bouthemy ´95] multi scale estimation

[Bruhn, Weickert, … ´03] fast AOS methods

[Paragios, Deriche ´00] active-contour modell

[Cremers, Soatto, Osher ´04] teaching level sets to walk

[Cremers, Soatto ´05] parametric Mumford-Shah model

[Aubert, Deriche, Kornprobst '99] TV functional for the motion field
the optical flow equation

image sequence:
\[ u : [0, T] \times \Omega \rightarrow \mathbb{R} ; \quad (t, x) \rightarrow u(t, x) \]

brightness constancy assumption:
\[ u(t + s, x(s)) = \text{const} \text{ on motion trajectories with} \]
\[ \dot{x}(s) = v(t + s) \text{ and } x(t) = x. \]

\[ \partial_t u(t, x) + v(t, x) \cdot \nabla u(t, x) = 0 \]
the optical flow equation (cont.)

space time gradient:

\[ Du = (u^+ - u^-) \nu + \nabla_{(t,x)} u \]

where \( \nu \) is the normal on the set of edge surfaces \( J \) in space time.

for the space time velocity \( w = (1, \nu) \) we get:

\[ \nabla_{(t,x)} u \cdot w = 0, \]

\[ \nu \cdot w^\pm = 0 \quad \text{(ambiguity)} \]
Mumford Shah model for a motion sequence:

assumptions:

\[ w = (1, v), \quad S_w \subset S_u =: S, \quad w^+ = 0 \lor w^- = 0 \]

\[
E[u, w, S] = \int_D |u - u_0|^2 \, dx \, dt + \int_{D \setminus S} (w \cdot \nabla u)^2 \, dx \, dt \\
+ \int_{D \setminus S} |\nabla u|^2 + |\nabla w|^q \, dx \, dt + \mathcal{H}^d(S)
\]

under the constraint \( \nu \cdot (w^+ + w^-) = 0 \)
a phase field model

\[ u_0 : [0, T] \times \Omega \rightarrow IR \]

\[ \zeta \]

\[ w \]

[Droske, Garbe, Preußer, R., Telea
Siam Journal for Appl. Math ´07]
motion deblurring

aim:

motion estimation, segmentation, and deblurring
related work

[Lee, Moon, Lee ´97] recovery of blurred video by an iterative method

[Favaro, Burger, Soatto ´04] anisotropic diffusion model for motion blur

[He, Marquina, Osher ´05] blind deconvolution via TV regularization

[Levin ´07] blind motion deblurring using image statistics

[Favaro, Soatto ´04] variational approach to scene reconstruction from motion blur
**Motion blur model**

\[ g_i = \frac{1}{\tau} \int_{t_i - \frac{\tau}{2}}^{t_i + \frac{\tau}{2}} u(s, x) \, ds = (u * h_v)(x - t_i v) \]

\[ h_v = \delta_0 \left( y \cdot \frac{v^\perp}{|v|} \right) h \left( y \cdot \frac{v}{|v|} \right) \]

**Improved model:**

\[ g_i = ((u_{obj} \chi_{obj}) * h_v)(x - t_i v) + u_{bg}(x) (1 - \chi_{obj}) * h_v)(x - t_i v) \]
Variational motion estimation/restoration model

\[
E[v, \Omega_{\text{obj}}, u_{\text{obj}}] = \\
\int_{\Omega} (g_i[v, \Omega_{\text{obj}}, u_{\text{obj}}] - u_i)^2 \, dx \\
+ |Du_{\text{obj}}| + \mathcal{H}^1(\partial\Omega_{\text{obj}})
\]

[Bar, Berkels, R., Sapiro ICCV ´07]
Part II

Outline

• Confidence Measures
• A new confidence measure for local optical flow methods
• A probabilistic approach
• Reconstruction of flow fields
Confidence Measures

- Confidence measure \( c: \mathbb{R}^3 \times I \times F \rightarrow [0,1] \)

- Often:
  - Exclusive reliance on image sequence
  - Flow information not used
  - e.g. image gradient

“Situation Measures“

Comparison of Confidence and Situation Measures and their Optimality for Optical Flows,
Claudia Kondermann, Daniel Kondermann, Bernd Jähne, Christoph Garbe
Submitted to IJCV, February 2007
Confidence vs. Situation Measures

• **Confidence Measure:**
  Estimates correctness of given flow vector

• **Situation Measure:**
  Estimates difficulty of image sequence locations
  \[ \Rightarrow \text{predicts correctness without knowing flow} \]

Find confidence measure for local methods

*Comparison of Confidence and Situation Measures and their Optimality for Optical Flows,*
*Claudia Kondermann, Daniel Kondermann, Bernd Jähne, Christoph Garbe*
*Submitted to IJCV, February 2007*
A new confidence measure

• “Learn“ correct/typical motion patterns from flow field neighborhood constellations

• Linear subspace of typical flow patches
  – e.g. Principal Component Analysis

• Spatio-temporal flow patches

An Adaptive Confidence Measure for Optical Flows Based on Linear Subspace Projections,
Claudia Kondermann, Daniel Kondermann, Bernd Jähne, Christoph Garbe
DAGM 2007
A new confidence measure

Model

Motion patterns
Moving flow discontinuity

An Adaptive Confidence Measure for Optical Flows Based on Linear Subspace Projections,
Claudia Kondermann, Daniel Kondermann, Bernd Jähne, Christoph Garbe
DAGM 2007
Confidence function:

\[ c(\vec{x}, \vec{u}_p) = 1 - \frac{\alpha(\vec{u}(\vec{x}), r_k(\vec{u}_p)(\vec{x}))}{\pi} \]
Results

Optimal confidence  Corner measure of structure tensor
Results

Optimal confidence

 pcaReconstruction result
Results

error

Yosemite sequence

Removed pixels

optimal

proposed

others

<removed pixels>
Flow Inpainting

- Idea: reconstruct flow at positions indicated by confidence measures using inpainting

$$\min \int_\omega \| \nabla_3 u^* \|_2 \, d\mathbf{x} \quad \text{with} \quad u^* \big|_{\partial\omega} = u \big|_{\partial\omega}$$

- $u$: given flow field
- $u^*$: flow region to be reconstructed
- $\delta\omega$: edge of flow region

Inverse Problems and Parameter Identification in Image Processing,
Michail Kulesh, Claudia Kondermann, Tobias Preusser, Martin Rumpf, Christoph Garbe et al.
Springer Verlag
Results

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*Inverse Problems and Parameter Identification in Image Processing, Michail Kulesh, Claudia Kondermann, Tobias Preusser, Martin Rumpf, Christoph Garbe et al. Springer Verlag*
Future Projects

• Reconstruction of incorrect flow vectors based on conditional expectation (work in progress with Rudolf Mester)

• A new local optical flow method based on PCA model and structure tensor (in preparation)

• Reconstruction of flow fields by means of inpainting methods (with Tobias Preusser, Martin Rumpf)

• Detection of occlusions and other difficult situations (with Erhardt Barth)